

Impact Estimation of Disasters

A Global Aggregate for 1960 to 2007

Yasuhide Okuyama

Sebnem Sahin

The World Bank
Sustainable Development Network Vice Presidency
Global Facility for Disaster Reduction and Recovery Unit
&
International University of Japan
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Abstract

This paper aims to estimate the global aggregate of disaster impacts during 1960 to 2007 using Social Accounting Matrix (SAM) methodology. The authors selected 184 major disasters in terms of the size of economic damages, based on the data available from the International Emergency Disasters and MunichRe (NatCat) databases for natural catastrophes. They estimate the losses and total impacts including the higher-order effects of these disasters using social accounting matrices constructed for this study. Although the aggregate damages based on the data amount to US\$742 billion, the aggregate losses and total impacts

are estimated at US\$360 billion and US\$678 billion, respectively. The results show a growing trend of economic impacts over time in absolute value. However, once the data and estimates are normalized using global gross domestic product, the historical trend of total impacts becomes statistically insignificant. The visual observation confirms the inverted ‘U’ curve distribution between total impact and income level, while statistical analyses indicate negative linear relationships between them for climatological, geophysical, and especially hydrological events.

This paper—a joint product of the Global Facility for Disaster Reduction and Recovery Unit, Sustainable Development Network Vice Presidency, and the International University of Japan—is part of a larger effort in the Network to disseminate the emerging findings of the forthcoming joint World Bank-United Nations’ Assessment of the Economics of Disaster Risk Reduction. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The authors may be contacted at okuyama@iuj.ac.jp and ssahin@worldbank.org, respectively. We are grateful to Apurva Sanghi, Reinhard Mechler and participants of the seminar at the World Bank held on this topic for their suggestions and constructive comments.

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IMPACT ESTIMATION OF DISASTERS: A GLOBAL AGGREGATE FOR 1960

TO 2007¹

YASUhide OKUYAMA²

*Graduate School of International Relations, International University of Japan, Niigata,
Japan*

SEBNEM SAHIN

GFDRR - The World Bank, Washington, D.C.

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² Contact author: Yasuhide Okuyama, International University of Japan, 777 Kokusai-cho, Minami-Uonuma, Niigata – 9497277, Japan, E-mail: okuyama@iuj.ac.jp, Tel: + 81 257 79 1424

1. Introduction

More than 7,000 major disasters have been recorded since 1970, causing at least \$2 trillion in damage, killing at least 2.5 million people, and adversely affecting societies (UN, 2008; p. xiii). And some 75% of the world's population lives in areas affected at least once by natural disaster between 1980 and 2000 (UNDP, 2004). It is also reported that the frequency and economic impacts of natural disasters have been increasing in recent years (UN, 2008). These statistics alone can make natural disasters one of the major issues and urgent tasks to tackle in the world. However, little is known about the economic impact of natural disasters, due partly to lack of the a standardized definition and also to the difficulty in measuring it.

It may be helpful to describe the importance of disaster impacts with some rhetoric. Masahisa Fujita of the Kyoto University made a comment in 2003³ that “an economy is like a tennis ball; the harder you throw the ball against a wall, the harder the ball bounces back to you.” A natural disaster throws an economy against a wall; then, how far an economy bounces back depends on the elasticity of the ball, *i.e.* the resilience of the economy. Knowing the disaster impacts is analogous to understanding how hard the ball (economy) is crushed against the wall. Some researchers, for example Albala-Bertrand (1993), argue that since the ball (economy) bounces back anyway, it is unimportant to know how hard the ball is crushed. However, without knowing how the ball (economy) is crushed, the relief efforts may become inefficient and ineffective and the pace of recovery may turn out to be slower. At the same time, if the disasters occur frequently and repeatedly, the ball (economy) accumulates fatigue and the resilience may deteriorate. This will result in the long-run impacts on the economy.

The relationship between disaster impacts and development is also a concern. Most empirical studies with cross-country data investigating the relationship between development level and disaster impacts conclude that correlation between them is negative, *i.e.* “the higher the level of development, the smaller both the number of

³ His comments were made to Davis and Weinstein (2004) at the 50th North American Meeting of the Regional Science Association International at Philadelphia, PA, on November 20, 2003.

deaths, injured, and deprived, and the relative material losses” (Albala-Bertrand, 1993; p.202). This appears consistent with the disaster theory that as countries develop and grow, they should have sufficient resources, such as financial and/or technological ones, to better manage disaster risk through the implementation of countermeasures and to better manage the adverse impact of disasters. However, some recent studies found somewhat different tendencies. According to Lester (2008), disaster impacts (as % of GDP) appear to have a negative correlation with GDP per capita; however, as GDP per capita increases, the complexity of economic system also increases and thus the disaster impacts have a positive correlation with GDP per capita up to a certain level before decreasing; as a result, the total impact over GDP per capita has an inverted ‘U’ shape curve. This implies that the most potentially affected economies by disaster will tend to be middle-income-level economies. Benson and Clay (1998) also claimed that the most vulnerable economies are not the most underdeveloped, since least developed countries tend to have simple economic structures, such as agriculture. While middle income-level economies with some diversifications seem more secure, because of intertwined economic activities between industries, however, the economic impacts can be much greater than in a simple agro-economy, and disaster impacts can be larger than in a simple economy.

In this paper, major disasters in the world during 1960 to 2007 are selected in order to analyze the historical trends of disaster impacts, and to investigate the relationship between disaster impacts and development level. In the following section, the general trends of natural hazard/disaster occurrence are presented and discussed in connection with development. Section 3 illustrates the data for the cases employed and the model used in this paper. Then, the impact estimation for global aggregate is presented and analyzed in Section 4. The final section concludes the paper with some remarks based on the findings and for the future agenda.

2. Natural Disasters in the World

First, the concept and definition related to disaster are clarified, since unclear terminology of event has caused confusions about the extent and implications. Several

terms, such as disaster, hazard, unscheduled event, catastrophic event, among others, have been used interchangeably in the literature; however, not all disasters or hazards lead to catastrophic consequences, and not all hazards or disasters unscheduled events. In this context, the two terms, “*disaster*” and “*hazard*”, include a wider range of events than the others. The distinction between disaster and hazard can be found in Okuyama and Chang (2004b, p. 2); “*hazard* is the occurrence of the physical event *per se*, and *disaster* is its consequence.” Ariyabandu (2001) put this more specifically suggesting that a disaster is an outcome of a hazard impacting on the *vulnerability* of a society. Furthermore, this paper focuses on natural hazards that can be classified into the following categories: hydro-meteorological origin, such as windstorms, floods, and drought; and geological origin, such as earthquakes, volcanic eruptions, and landslides.

According to the United Nations’ International Strategy for Disaster Reduction (UNISDR), the frequency of disasters caused by natural hazard has been increasing.⁴ Figure 2-1 indicates the trends of disaster frequency by type between 1900 and 2005. All types of disaster are increasing, and especially hydro-meteorological ones have occurred much more frequent than the other two have. On average, 78 disasters per year had occurred during the 1970s. This number grew to 351 per year during 2000 and 2006. Meanwhile, the average number of people killed in any single disaster has been declining, making the total number of casualties per year from disasters fairly constant (UN, 2008).

⁴ <http://www.unisdr.org/disaster-statistics/occurrence-trends-century.htm>

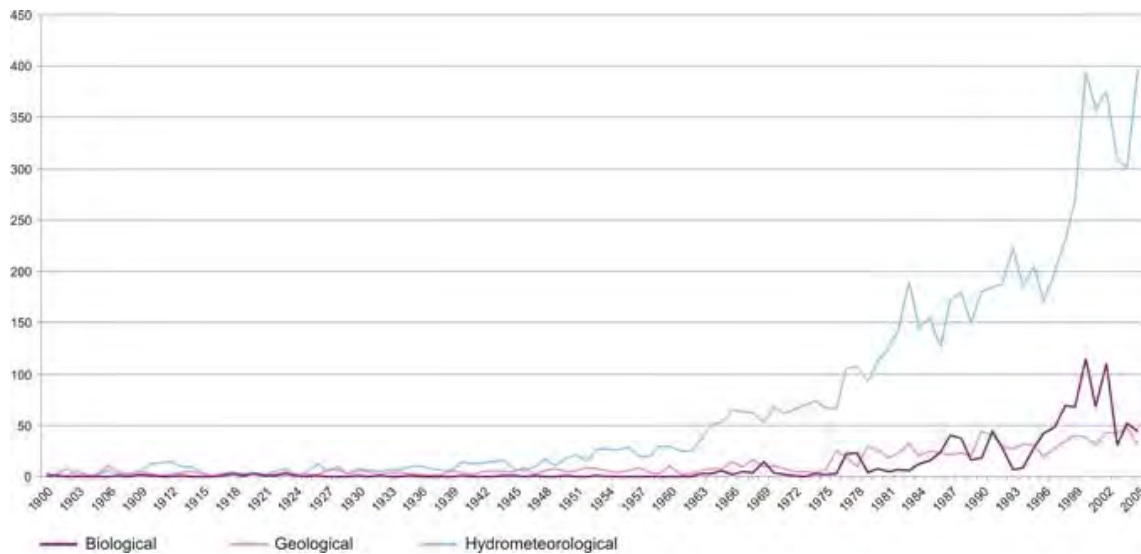


Figure 2-1. Number of Disasters Registered in EMDAT⁵

However, economic damages caused by disasters in the world have been also increasing, especially in the recent years, due partly to more frequent occurrence and also to the increased complexity of economic structure around the world. Figure 2-2 illustrates the increasing trends between 1900 and 2008, especially after the mid 1980s, with several spikes when large-scale disasters occurred. Damages have averaged \$83 billion per year since 2000, whereas the average of damages was \$12 billion per year during the 1970s (UN, 2008; constant 2005 US\$). These observations lead to the fact that disasters have become more menacing the well-being of societies, while they have become less life-threatening.

⁵ <http://www.unisdr.org/disaster-statistics/occurrence-trends-century.htm>; Biological disasters include epidemics and insect infestations.

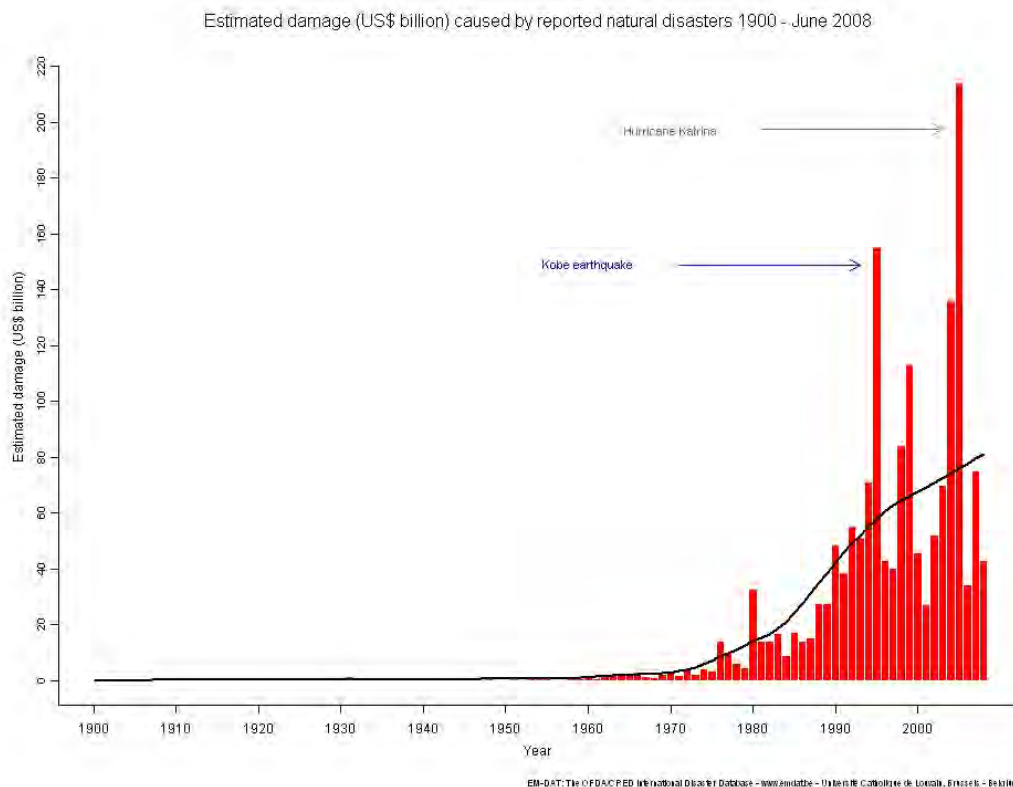


Figure 2-2. Estimated Economic Damage by Disasters Registered in EMDAT⁶

While more than 60% of the total damages caused by disasters occurred in high-income countries, the estimated damages of disasters as a share of GDP were significantly greater in less developed (and small) countries (UN, 2008). Figure 2-3 shows the top 50 disasters with largest damages during 1991 and 2005. The largest damage in this period was the 2005 Hurricane Katrina in the United States, followed by the 1995 Hanshin-Awaji (Kobe) Earthquake in Japan. While some developing countries, like China and Indonesia, are included in the top 50 cases, most of the largest damages occurred in developed countries with relatively small GDP share. In contrast, Figure 2-4 presents the top 50 disasters with largest GDP share in the same period. All the 50 disasters occurred in developing countries, especially in small island countries. As a matter of fact, no upper middle-income country has been ranked in the top 100 for most costly disasters as a share of GDP (UN, 2008).

These observations of the relationship between development level and disaster

⁶ <http://www.emdat.be/Database/Trends/trends.html>

damages coincide with the recent studies, such as Benson and Clay (1998), Lester (2008), and Kellenberg and Mobarak (2008). They found an inverted, non-linear ‘U’ curve relationship between the overall disaster impact and income level of a country (similar to the Kuznets curve on economic inequality). This is due to the fact that the complexity of economy increases as it grows and leads to a broader range of impacts; then after a critical income level is attained, there are sufficient financial and technological resources available for installing effective countermeasures against natural disasters⁷. It is still unclear that this inverted U curve relationship can be found with different measurement of economic impact, based on the empirical data. However, this point is important to understand how natural hazards become disasters.

In addition, Kellenberg and Mobarak (2008) found that floods, landslides, and windstorms exhibit the stronger tendency of this inverted U shape non-linearity than extreme temperature events or earthquakes do. This difference may result from the characteristics of natural hazards. Albala-Bertrand (1993) suggested the following seven characteristics of natural hazards: 1) magnitude; 2) frequency; 3) duration; 4) location extent; 5) spatial dispersion pattern; 6) speed of onset; and 7) regularity. Hydro-meteorological hazards, such as windstorms, floods, and drought, occur more frequently, have a wider area of damages, with particularly devastating consequences for rural economy, have a larger impact on losses, and require a longer recovery time. On the other hand, geological hazards, such as earthquakes and landslides, are infrequent events that oftentimes cause considerable damages to assets (UN, 2008). This tendency also calls for further examination in order to illustrate clearly the differences in economic impact across types of natural hazard. Furthermore, this line of research can benefit to understand multi-hazard situations (multiple hazards occur concurrently or consecutively in the same country or same location), which have happened increasingly in the recent years.

⁷ Please see the further discussion on this point in the companion paper, “Critical Review of Methodologies on Disaster Impact Estimation”.

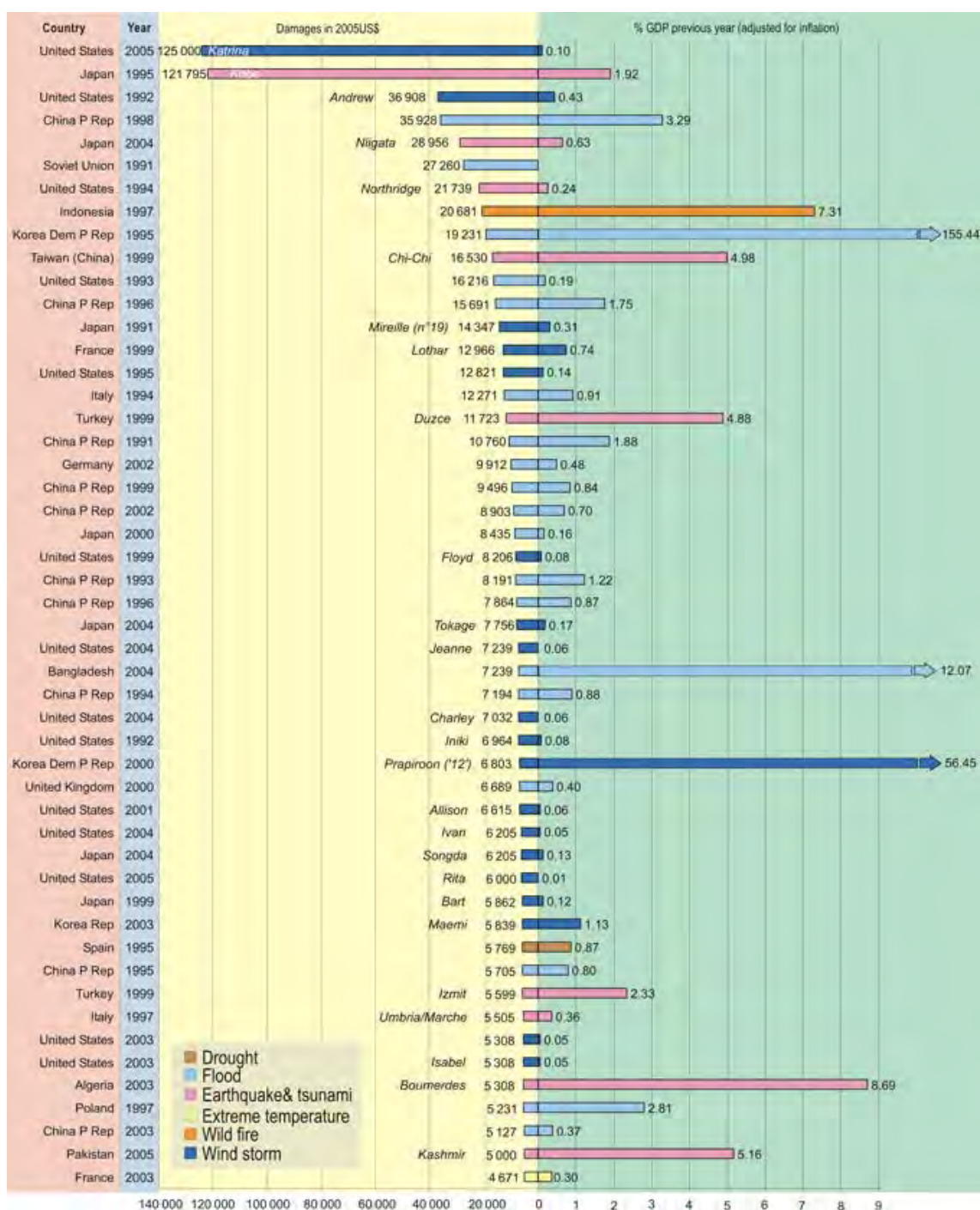


Figure 2-3. Top 50 Economic Damages by Disaster and Country: 1991-2005⁸

⁸ <http://www.unisdr.org/disaster-statistics/top50.htm>

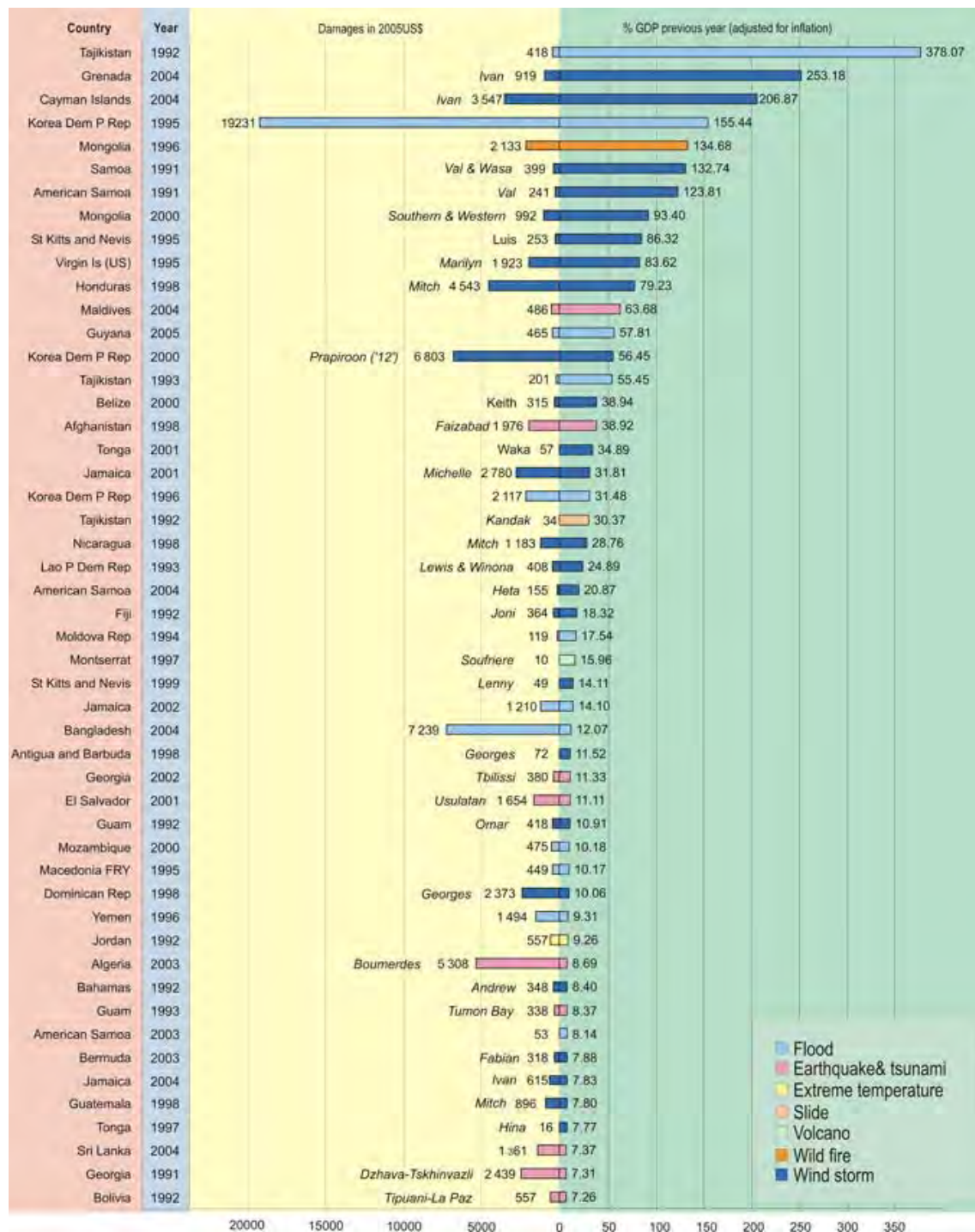


Figure 2-4. Top 50 Economic Damages as Share of GDP by Disaster and Country: 1991-2005⁹

⁹ *ibid.*

3. Global Aggregation of Disaster Impacts: Data and Methodology

As seen in the previous section, economic damages of disasters have some tendencies and trends. At the same time, the data for disaster impacts have been still limited and sometimes confusing due to the use of interchangeable terminologies and to the lack of standardized definitions. Moreover, while each disaster is unique, economic impacts of disasters have been analyzed mostly through the case studies of a particular event, rather than in an aggregated context for the generalized understanding of phenomena. In this regard, estimating the global aggregate of disaster impacts has been long-sought in the disaster community. This section presents the data sources for the global aggregate estimation of disaster impacts in this paper. The data used are mostly available for public as secondary data, but the definitions and/or extent of disaster damage data are not standardized to make a direct comparison of the derived impacts difficult.

3.1. The Case for a Global Aggregate

Natural hazards occur around the world with a wide range of intensities. In order to set the cases for global aggregate of impact estimation, economic damage, or loss data of disasters need to be collected. No standardized definitions or frameworks of economic damage and loss are set so far, except the use of ECLAC methodology (UN ECLAC, 2003) for recent disasters. Thus, it is difficult to collect the consistent measurement of economic damage and loss data for past disasters. However, there are a few sources offer the economic damage or loss data of past disasters: EM-DAT database by Centre for Research on the Epidemiology of Disasters (CRED) of Université Catholique de Louvain, NatCat database by Munich Re, and Sigma data base by Swiss Re.¹⁰ In this present study, economic damage data are gathered from EM-DAT and NatCat databases.

The disaster cases are selected from the ones occurred during 1960 to 2007. As mentioned above, there is no standard definition of economic impact; furthermore,

¹⁰ Some useful comparison of these databases can be found in Guha-Sapir and Below (2002).

economic damage, loss, and impact of disasters are used interchangeably in various documents, including official ones. In fact, EM-DAT uses ‘estimated damage’¹¹ while NatCat’s data is labeled as ‘overall losses’. It is then useful to clarify the terminology: *damages* are by economics definition the damages on stocks, which include physical and human capitals; *losses* are business interruptions, such as production and/or consumption, caused by damages and can be considered as first-order losses; *higher-order effects*, which take into account the system-wide impact based on first-order losses through inter-industry relationships; and *total impacts* are the total of flow impacts, adding losses (first-order losses) and higher-order effects.¹² Whereas EM-DAT and NatCat databases used different terms for economic data of disasters, we consider both of them as damages, *i.e.* damages on capital stock.

Then, the disaster cases¹³ are combined between two databases, and are screened based on the intensity in order to reduce the number of cases by eliminating smaller cases. The intensity condition is set as: damages should be greater than or equal to US\$ 20 million (current), and either should be greater than 1% of current GDP for high-income countries or 2% of current GDP for low-income countries. The number of cases after this screening becomes 184. In order to be used as the input to estimate total impacts, these damage data were converted first to flow measure, *i.e.* losses, using capital-to-output ratio based on the available and estimated capital data¹⁴ and the current GDP data. The derived losses are further converted to changes in final demand through dividing losses by the inverse of diagonal terms in the direct input coefficient matrix. Then, the total impact of each disaster is estimated by plugging this final demand changes into the respective accounting multiplier matrix, described below.

¹¹ EM-DAT states the definition of estimated damage as: “Several institutions have developed methodologies to quantify these losses in their specific domain. However, there is no standard procedure to determine a global figure for economic impact.”

(<http://www.emdat.be/ExplanatoryNotes/explanotes.html>)

¹² Further discussion of terminology can be found in a companion paper, “Critical Review of Methodologies on Disaster Impact Estimation.”

¹³ These cases include climatological, geophysical, hydrological, and meteorological disasters in EM-DAT definition.

¹⁴ Nehru and Dhareshwar (1995), GTAP, and World Bank (2006). Estimation of missing values was carried out using ‘Gross Capital Formation’ data from the World Bank website.

3.2. Economic Impact Estimation Methodology: Social Accounting Matrix

Various methods can be used to estimate higher-order effect of disasters based on damages and/or losses data, including input-output (IO) table, social accounting matrix (SAM), and computable general equilibrium (CGE) model.¹⁵ Since the cases for global aggregate include a large group of countries in different years, the data availability of method becomes one of the key issues for the selection of methodology. SAM is employed in this study because of its data availability of construction and the familiarity of use in international development community¹⁶.

Social accounting matrix (SAM) has been utilized to examine the higher-order effects across different socio-economic agents, activities, and factors. Notable studies using a SAM or one of its variants include Cole (1995, 1998, and 2004) among others. Like IO models, the SAM approach has rigid coefficients and tends to provide upper bounds of impact estimates. On the other hand, the SAM framework with certain disaggregation, as well as extended IO model and CGE model, can derive the distributional impacts of a disaster in order to evaluate equity considerations for public policies against disasters. In this paper, SAMs were constructed in an aggregated version for each country and each decade, based on the World Bank data.¹⁷ Due to the large number of SAMs that needed to be constructed, and in order to maintain the consistency of the structure and features among them, the SAMs were constructed in the most aggregated way—one sector (one value) for each principal account (see the Figure 3-1). This simple structure is also necessary to suit with the aggregation level of input data, total damages, for each case.

¹⁵ A summary and discussion of methodologies on impact estimation can be seen in a companion paper, “Critical Review of Methodologies on Disaster Impact Estimation.”

¹⁶ Please see Appendix 1 for detailed description of SAM, and a companion paper, ‘Impact Estimation Methodology: Case Studies.’

¹⁷ SAM structure draws upon the MAMS model (Lofgren and Diaz-Bonilla, 2008), and Lofgren’s SAM template is used to construct SAMs in this exercise (see Hans Lofgren’s course material (2008) on MAMS, for the detail).

	Production Activities	Factors	Households	Other Institutions	Rest of the World	Total
Production Activities						
Factors						
Households						
Other Institutions						
Rest of the World						
Total						

Figure 3-1. Structure of SAM for the Global Aggregate Estimation¹⁸

4. Analysis of Global Aggregate Disaster Damages, Losses, and Higher-Order Effects

The economic impact of 184 disasters for the last 50 years are estimated and analyzed in this section. As described in the previous section, the higher-order effects of these disasters are derived based on the data from EM-DAT and NatCat and the constructed SAMs for this study. The historical trends, differences in types of disaster, and the relationship between disaster impact and development level are investigated below.

4.1. Historical Trends of Impact

During 1960 to 2007, based on the sampled 184 disasters, total damages on capital stock were about US\$ 742 billion (in 2007 constant value). Estimated losses and total impacts in this period were US\$ 360 billion and US\$ 678 billion, respectively. The impact multiplier from these figures becomes 1.88 (ratio between total impacts and losses), implying that on average losses from a disaster can be nearly doubled via

¹⁸ The highlighted cells are treated as endogenous, and other cells are set as exogenous in this paper.

interdependencies in an economy. Table 4-1 shows the distribution of impact across the types¹⁹ of disaster. Over all, geophysical disasters have the largest portion of all the economic impacts, *i.e.* damages, losses, and total impacts, with around 40% of the total impacts. This implies that geophysical disasters cause significant damages on stock, as well as losses and total impacts. This tendency may result from the fact that geographical disasters cause the destructions of not only production facilities and houses but also infrastructure including road networks and lifelines. These damages to infrastructure propagate economic impacts to a wider extend through economic interdependencies and may prolong the recovery and reconstruction. Meanwhile, hydrological and meteorological disasters have the similar shares of economic impacts, with around 25% of the total. Since these types of disasters have a wider range of location extent but less destruction of physical assets, the significance of economic impacts is moderate comparing to geophysical disasters.

¹⁹ Climatological disasters include droughts, extreme temperatures, and wildfires; geophysical disasters are earthquakes and volcano eruptions; hydrological disasters are floods and landslides; and meteorological disasters include storms.

Table 4-1. Economic Impacts by Type of Disaster (1960 – 2007)

	Damages	Estimated Losses		Estimated Total Impacts	
	total value	total value	loss-damage ratio	total value	total impact-damage ratio
	share across column	share across column		share across column	total impact-loss ratio
Climatological	84,910	40,837	0.48	72,604	0.86
	11.4%	11.4%		10.7%	1.78
Geophysical	282,987	144,196	0.51	271,489	0.96
	38.1%	40.1%		40.1%	1.88
Hydrological	188,360	87,994	0.47	158,678	0.84
	25.4%	24.5%		23.4%	1.80
Meteorological	186,098	86,717	0.47	175,073	0.94
	25.1%	24.1%		25.8%	2.02
Total	742,356	359,744	0.48	677,844	0.91
					1.88

Source: values of damages are based on the data of EM-DAT and Munich Re.

Remark: values are in constant 2007 US\$ million.

The relationships among damages, losses, and total impacts of each disaster type show some interesting features. The loss-damage ratio, dividing the value of estimated losses by the damage value, looks very similar across the different disaster types, at around 0.5. On the other hand, total impact-damage ratios, dividing the value of estimated total impacts by damage value, have noticeable differences among them: geophysical disasters have the largest ratio (0.96), followed closely by meteorological disasters (0.96), while climatological and hydrological disasters have relatively smaller values, 0.86 and 0.84, respectively. At the same time, the impact multipliers, total impact-loss ratios, have a slightly different order: meteorological disasters have the largest impact multiplier (2.02), followed by geophysical (1.88), hydrological (1.80), and climatological (1.78). Because highly aggregated SAMs for each country are used for the estimation in this study, the interpretation of these results requires some caution. Nonetheless, in general, geophysical disasters seem the most costly in absolute value, and the impacts may become large (larger total impact-damage ratio and impact multiplier) than other types of disaster. Meteorological disasters are not so straightforward: in total, their economic impacts in absolute value are about average (around 25% for damages, losses, and total impacts); however, their total

impact-damage ratio and impact multiplier is rather larger, and even the largest. These imply again that meteorological disasters wipe out a large extent of areas and a large range of activities resulting in greater total impacts than other types of disasters. In fact, out of the top ten events with largest impact multipliers, seven events are meteorological ones (in Madagascar and Guatemala), two are hydrological (in Madagascar and Bangladesh), and one is geophysical (in Guatemala).

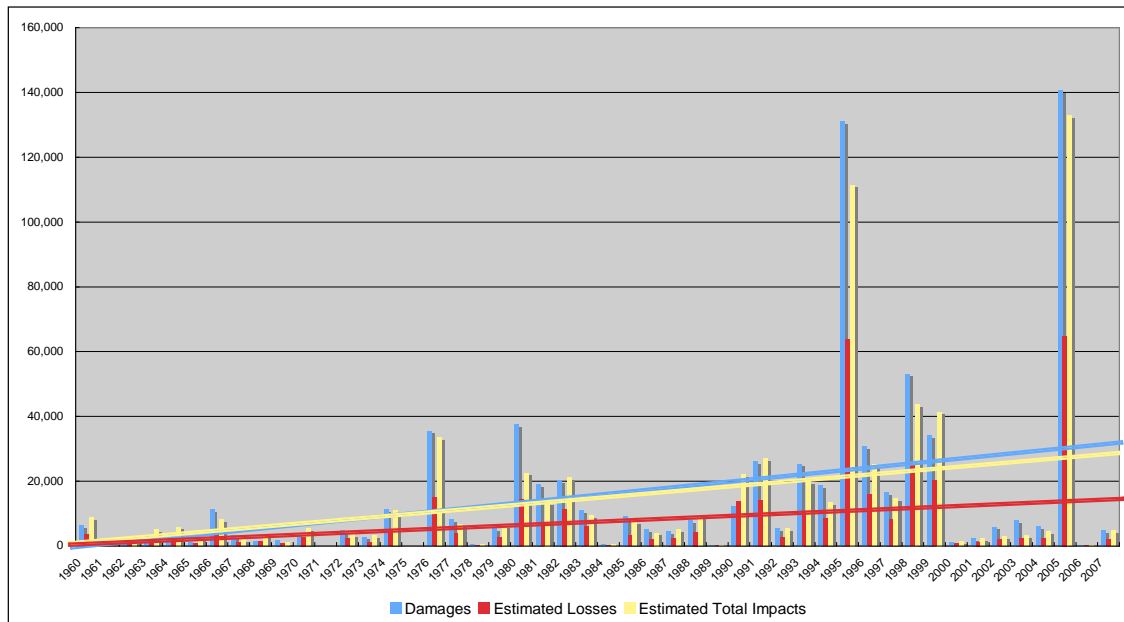


Figure 4-1. Historical Trends of Economic Impacts²⁰

The historical trends of economic impacts for the 184 cases mimic the one in figure 2-2 based on EM-DAT data. Figure 4-1 illustrates the trends of aggregated damages, losses, and total impacts for each year. A gradual increase of all the three economic impacts is observed until year 2000, with an exception of 1995 including the Hanshin-Awaji (Kobe) Earthquake in Japan. Between 2001 and 2004, a lull of economic impacts was observed; and then, year 2005 becomes another exception with Hurricane Katrina in the U.S. This lull is not found in figure 2-2; the difference between figures 2-2 and 4-1 results from the screening of events, in which the cases in figure 4-1 are selected with some certain size in damages (grater than US\$ 20 million; larger than 1% of GDP for developed countries or 2% of GDP for developed countries). For instance, multi-country disasters, such as the 2004 Indian Ocean Earthquake and

²⁰ Values are in constant 2007 US\$ million. Lines in the figure are the linear regression line for each item, and all three lines are statistically significant with 5% level (please see the details in Appendix 2).

Tsunami, are separated by affected country and screened; thus, some countries affected by the events are not included. Therefore, some years in figure 4-1 have much smaller total damages than in figure 2-2.

The relationships among damages, losses, and total impacts appear different each year. For example, in 1990²¹, the aggregated total impacts are the largest, followed by the aggregated losses and the aggregated damages. In 1999²², for instance, the aggregated total impacts are the largest, followed by the aggregated damages and the aggregated losses. On the other hand, in many years, aggregated damages are the largest, followed by aggregated total impacts and aggregated losses. Since the estimation of losses (and of higher-order effects based on losses, and the construction of SAMs) relies a great deal on capital stock data, which are rarely available and thus are estimated based mostly on the available data in recent years, and thus the estimated results are sensitive to capital stock estimation, the above observations of relationship among these economic impacts cannot be easily generalized. In addition, the relationship between losses and total impacts needs further attention, because the damages and/or losses to specific industries can cause different higher-order effects: for example, damages and/or losses of manufacturing industry may result in a production bottleneck via forward linkage (supply chain) and backward linkage (demand chain) and can cause effects in a broader range of industries, depending on how the domestic (or international) interindustry relationships are intertwined. This kind of disaggregated analysis of higher-order effects for the recent disasters can be found in a companion paper, 'Impact Estimation of Higher-Order Effects: Case Studies'.

It is a common practice to normalize data in current value with time varying factors. The analysis above is based on the constant value (in 2007 US\$), controlling inflation over time. In disaster impact analysis, some other factors may need to be controlled. For instance, Pielke *et al.* (2008) used the changes in inflation and wealth at the national level and the changes in population and housing units at coastal county level for analyzing the trends of hurricane damage in the United States between 1900

²¹ In 1990, five events are included: floods in Honduras; earthquake in Iran; drought in Mozambique; drought in Namibia; and earthquake in Philippines.

²² Nine events are included in 1999: earthquakes in Columbia, Greece, and Turkey; storms in Denmark and St. Kitts and Nevis; droughts in Iran, Mauritius, and Morocco; and, flood in Venezuela.

and 2005. For a cross-country and time-series analysis like this research, it is difficult to control all the factors; therefore, the Gross World Production (World GDP) is employed to normalize the disaster impact data by controlling the size of economy in question. Figure 4-2 illustrates the trends of disaster impacts as the share of world GDP. The trends appear very similar to the ones in absolute value (figure 4-1). However, the statistical analysis²³ indicates that only the trends of damages and losses are statistically significant, but being rather weak at 10% level, with a linear trend line between time and GDP share of total impacts, while the trend of total impacts is not statistically significant. Not significant trend in total impacts is in fact consistent with other studies using normalized disaster impact, including abovementioned Pielke *et al.* (2008). However, the inconsistency between statistically significant trends of damages and losses and insignificant total impacts needs to be further investigated, perhaps including smaller intensity of disasters.

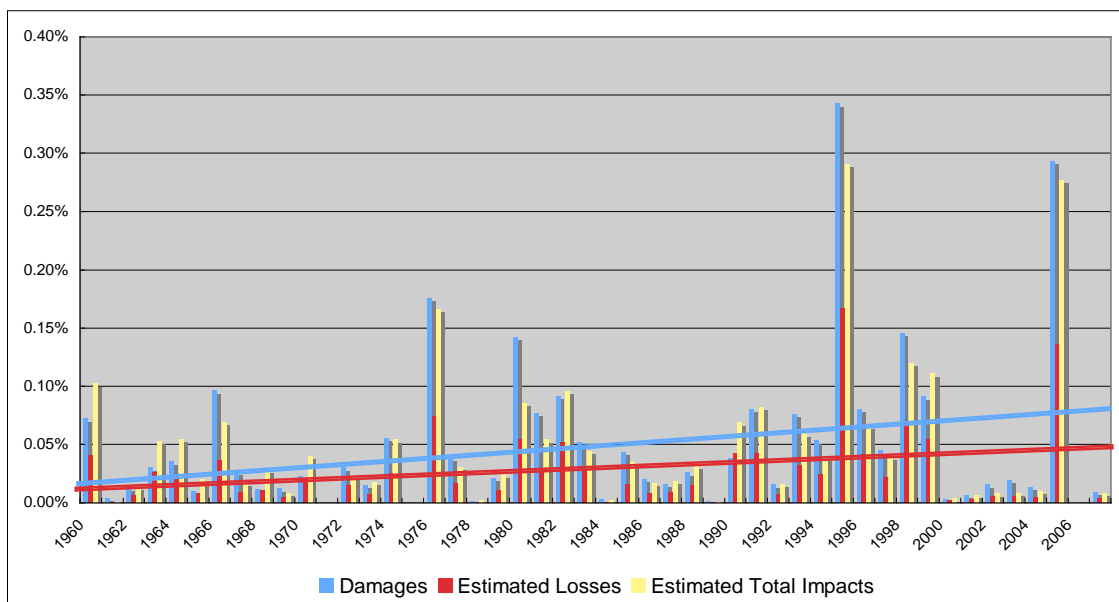


Figure 4-2. Historical Trends of Normalized Disaster Impacts²⁴

The historical trends of normalized economic impacts appear quite different across the types of disaster (see Figure 4-3). Climatological disasters were increasing the economic impacts until the early 1980s; and then there was a lull for the remaining

²³ Please see the details of statistical analysis with normalized data in Appendix 2.

²⁴ Lines in the figure are the linear regression line for each item, and both lines are statistically significant with 10% level (please see the details in Appendix 2).

of 1980s; the significant economic impacts were observed in 1994 again, but became decreasing afterwards. Geophysical disasters seem not to exhibit a particular trend due to their mechanism of occurrence. As for hydrological disasters, the economic impacts have an increasing trend until 1998, and show a lull afterwards, corresponding to the trends of overall economic impacts. Meteorological disasters display the similar trend to the hydrological events, having somewhat increasing trends until 1998, then a lull, with an exception of Hurricane Katrina in 2005. The relationships among damages, losses, and total impacts appear not particularly different across the types of disasters, indicating that the relationships among economic impacts depend solely on the economic structure of each country, *i.e.* SAM.

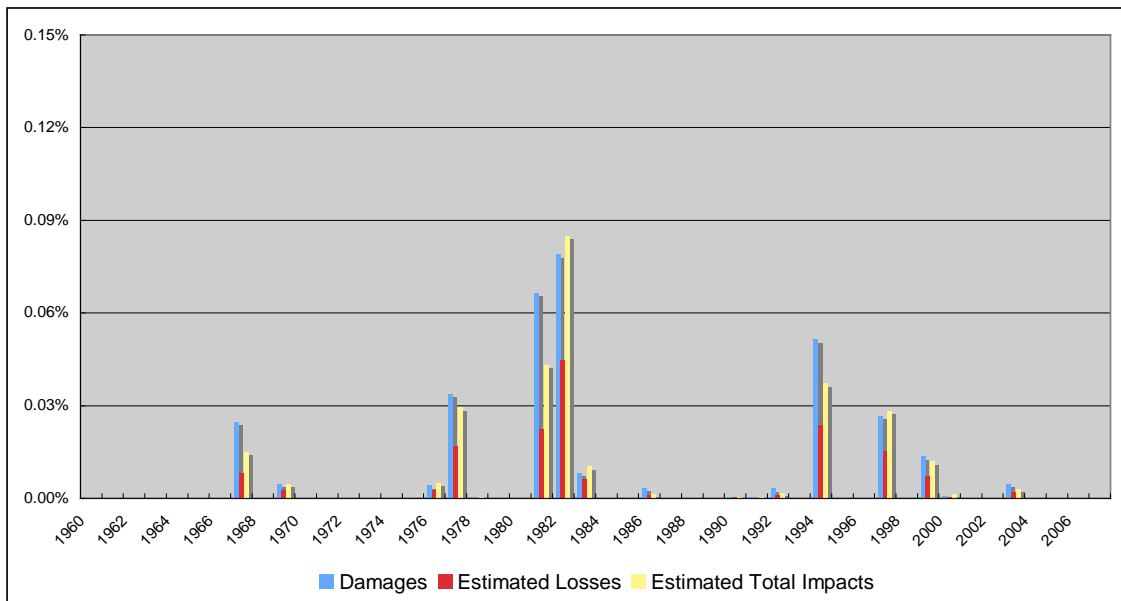


Figure 4-3 (a). Historical Trends of Climatological Disasters (normalized)

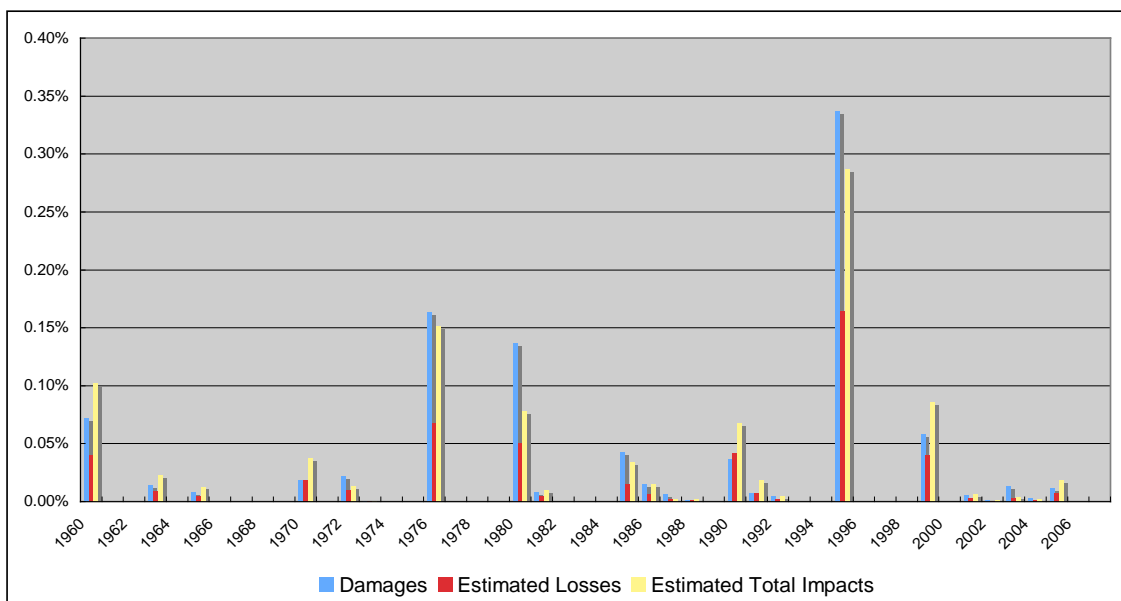


Figure 4-3 (b). Historical Trends of Geophysical Disasters (normalized)

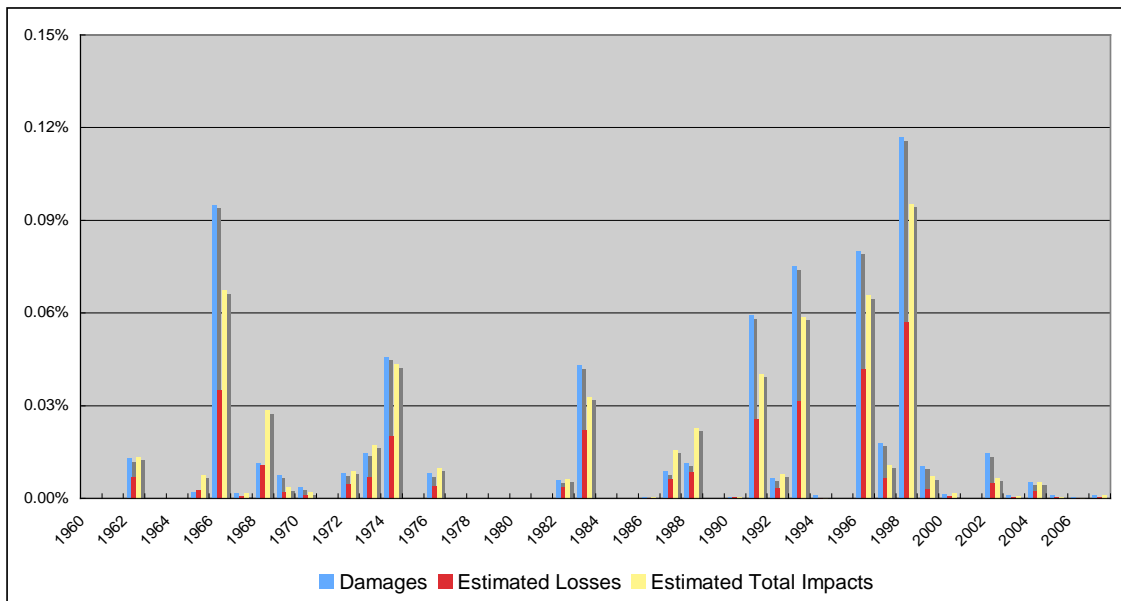


Figure 4-3 (c). Historical Trends of Hydrological Disasters (normalized)

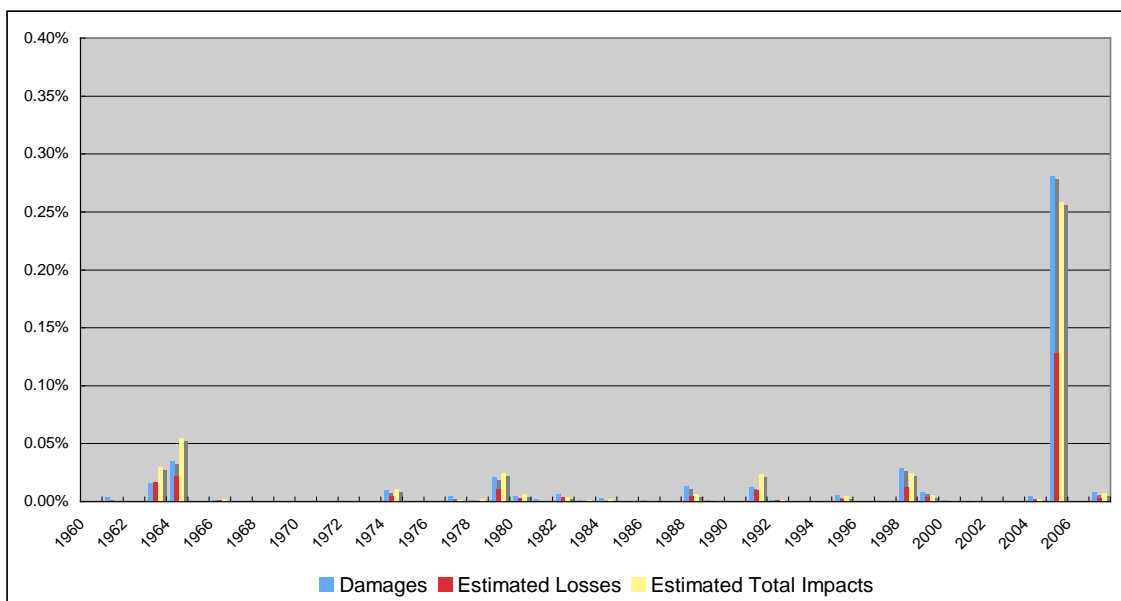


Figure 4-3 (d). Historical Trends of Meteorological Disasters (normalized)

4.2. Analysis on Development

As discussed in Section 2, recent studies found an inverted ‘U’ curve relationship between the overall disaster impact and income level of a country. While damages to assets can be reduced with the installation of countermeasures against natural hazards as income level increases and thus sufficient financial resources can be used, losses can increase as economy becomes developed and complex. Then, the overall impact, adding damages and losses, becomes the inverted ‘U’ shape curve. However, the use of overall impact as the sum of damages and losses can be considered as double-counting of economic impacts, according to Rose (2004). Damages and losses are measurements on different variables—stock and flow, implying two sides of the same phenomenon. On the other hand, total impacts of a disaster include losses and the ripple effect of initial losses. This total impact should be used to investigate the inverted ‘U’ curve relationship between economic impact and income level.

The distribution of 184 cases, seen in Figure 4-4, displays the tendency of inverted ‘U’ curve relationship between the natural log of GDP per capita and the share of total impacts over GDP (hereafter GDP impact). While both tails, lower and higher GDP per capita countries, indicate relatively low GDP impact, many middle level GDP per capita countries have higher GDP impact values. Two outliers, with extremely large GDP impact rate, are 1963 storm in Haiti and 1988 storm in St. Lucia, small island nations hit by hurricanes. This observation appears to prove that the theory of inverted ‘U’ curve relationship can be found with total impact of disasters. It should be noted, however, that the 184 cases used in this study are screened and have some certain intensity in terms of damages. Therefore, further research might be necessary to include all the disaster cases reported in order to test this tendency.

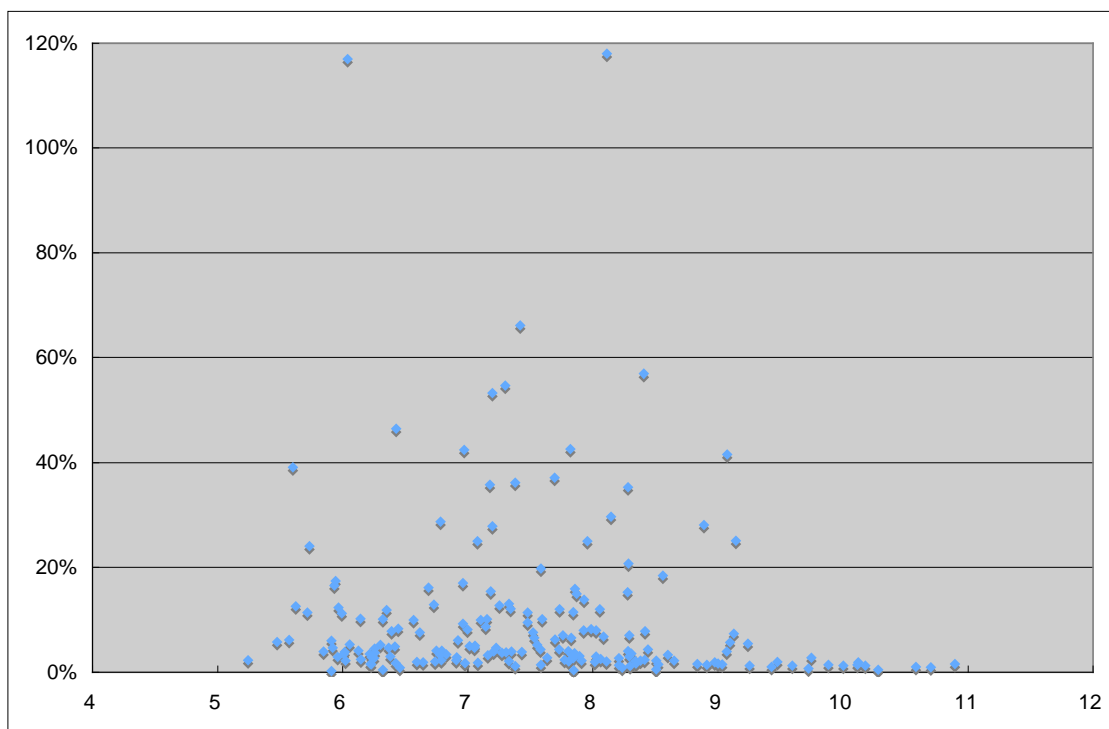


Figure 4-4. Relationship between GDP per capita and Impact on GDP²⁵

Categories of disaster show differences in the relationship between disaster impact and income level (see Figure 4-5). Climatological, geophysical, and meteorological disasters appear to have the inverted ‘U’ curve relationship as in Figure 4-4; however, their distributions look a bit diverse. The distribution of climatological disasters seems relatively flat with a small bulge in the middle, indicating less significant GDP impact across income levels. Geophysical disasters exhibit a large protuberance in the middle and longer right tail, implying the characteristics of geophysical hazards (unpredictable and less frequent) and the effectiveness of counter measures in richer countries. And, meteorological disasters show a wider variance over GDP per capita and a larger range of GDP impact. This may result from the facts that most of the countries affected are small island countries or located on the coast with a mixture of income levels and that damages from hazards depend heavily on the route of storms. On the other hand, the distribution of hydrological disasters appears considerably skewed to left, indicating that the most vulnerable countries against

²⁵ X-axis indicates natural log of GDP per capita; Y-axis shows the share of higher-order effect over GDP; in constant 2007 US\$ million.

hydrological disasters are low-income countries. This is because hydrological disasters, such as floods and landslides, “have a wider impact, with particularly devastating consequences for rural economy (p. 80)” (UN, 2008). Those countries having lowest income countries with higher GDP impact are Bangladesh, Mozambique, and Nepal.

A series of statistical analyses is performed to see whether or not the inverted U curve relationship actually exists for the above cases²⁶. The results show that inverted U curve relationship (non-linear function form) in either all events case or any type of disasters is not statistically significant, contrary to the above visual inspections. On the other hand, negative linear relationships are statistically significant with climatological, geophysical, and hydrological events. For the cases with all the 184 events and with meteorological events, neither linear nor non-linear form is statistically significant. The negative linear relationship is, in fact, consistent with the traditional disaster theory, in which as development level, *i.e.* income level, increases, the risk for disaster impacts decreases. A striking finding of the statistical analysis is that the slope of the statistically significant regression line is much steeper in geophysical disasters than in the other two cases (climatological and hydrological): around two times steeper. This also signifies the characteristics of disaster. Geophysical disasters damage mostly the structure of built environment; therefore, as national income rises, the better structure of buildings and housing can become affordable and utilized and the total impacts may become relatively small, and the efficacy of such solid structure appear effective to reduce the impacts of geophysical disasters. On the other hand, climatic and hydrological disasters may damage the functions of society and economy in a wide area; thus, national income increase might not have such a direct improvement. In addition, while statistically insignificant, the results of non-linear form display some interesting findings. Among four types of disasters, climatological, geophysical, and meteorological events indicate an inverted U curve relationship, while hydrological events show a U curve relationship.

These results, to some extent, may contradict with Kellenberg and Mobarak’s (2008) study, in which with the data of 133 countries over 28 years they found the

²⁶ Please see Appendix 3 for detailed results and discussions.

stronger tendency of this inverted ‘U’ shape non-linearity between the number of disaster casualties and income level for floods, landslides, and windstorms than for extreme temperature events or earthquakes. However, they use the number of casualties as disaster intensity, whereas this study employs the higher-order effects and total impacts of disasters. These factors, number of casualties and total impacts may represent different aspects of a disaster, and may not have a perfect correlation with each other. An important common implication between this and their studies is that type of disaster plays a major role for this inverted ‘U’ curve relationship between disaster intensity and development level. And, further extending this line of analysis, inclusion of smaller events, which are excluded in the present study, might potentially reveal more concrete tendencies of the relationship between impact on GDP and GDP per capita. Or, since the global aggregate estimation of disaster impacts is carried out based on the aggregated economic damage data, with no sector disaggregation, the estimated results did not take into account inter-industry relationships, which is considered as the basis for increased vulnerability in middle-income countries. Disaggregating sectors to some extent, for example at least to primary, secondary, and tertiary industries, is necessary to see the intricacy of higher-order effects and their differences among different development levels.

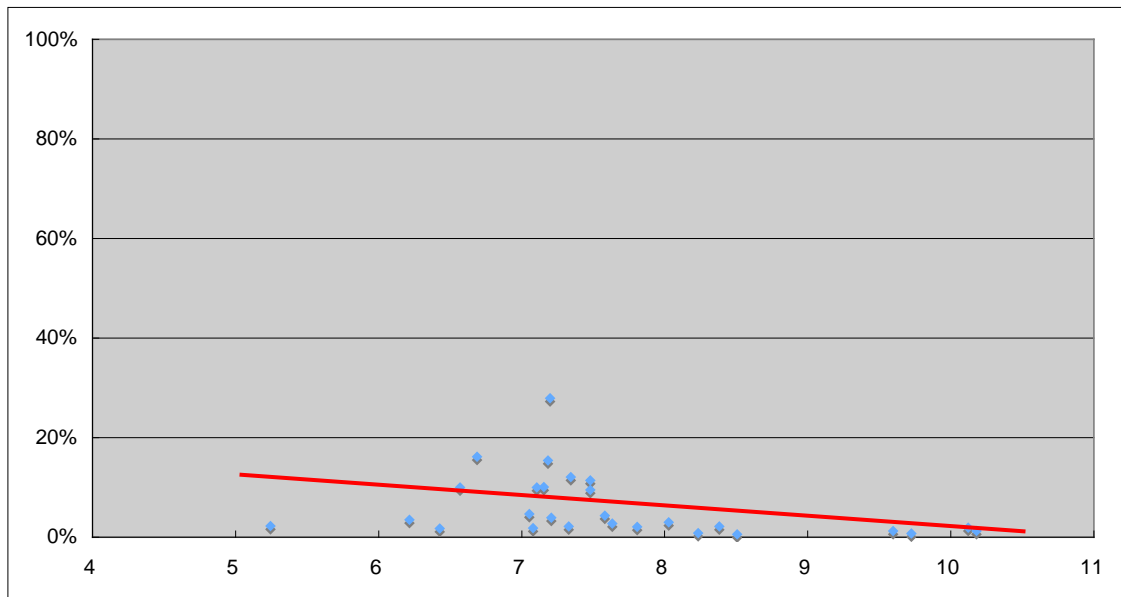


Figure 4-5 (a). Relationship between GDP per capita and Impact on GDP (Climatological Disasters; red line is the statistically significant regression line)

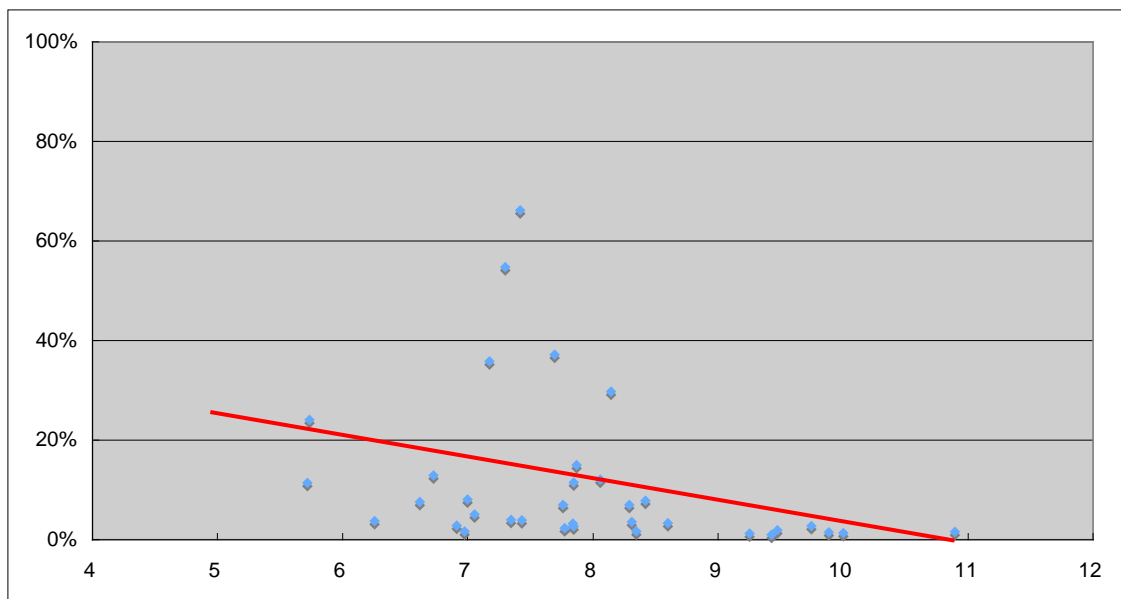


Figure 4-5 (b). Relationship between GDP per capita and Impact on GDP (Geophysical Disasters; red line is the statistically significant regression line)

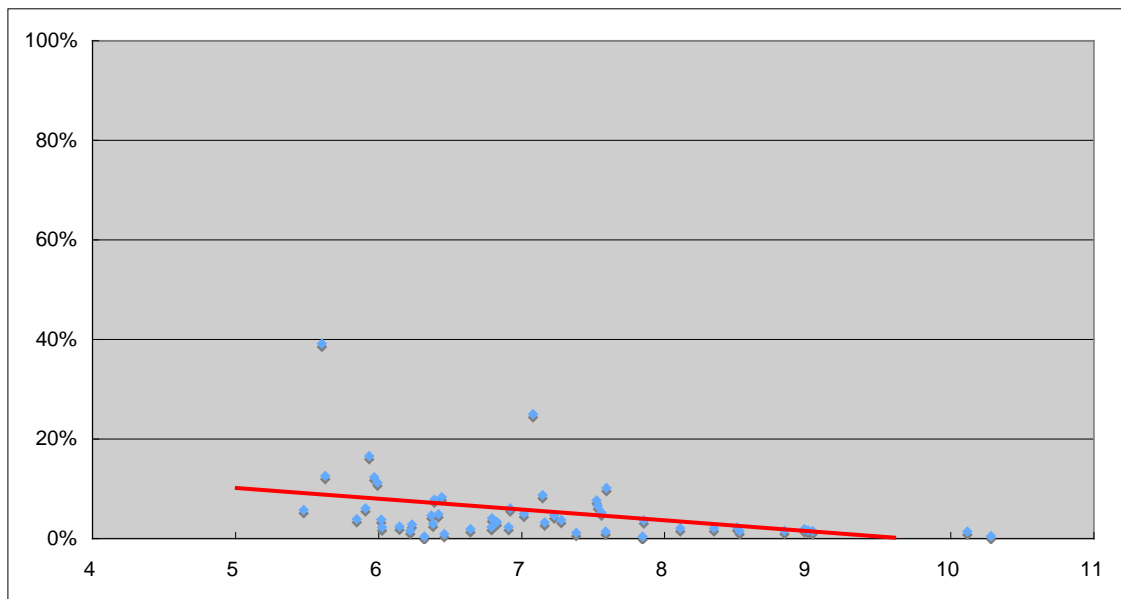


Figure 4-5 (c). Relationship between GDP per capita and Impact on GDP (Hydrological Disasters; red line is the statistically significant regression line)

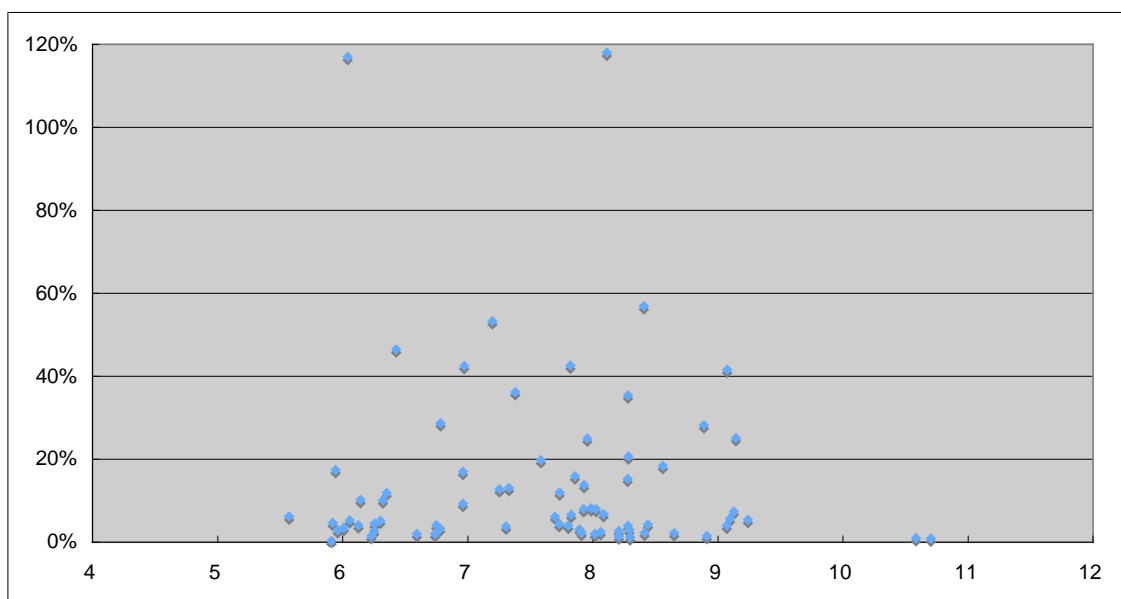


Figure 4-5 (d). Relationship between GDP per capita and Impact on GDP (Meteorological Disasters)

5. Summary and Conclusions

This paper estimated the global aggregate of the economic impact of major disasters during 1960 to 2007 using SAM methodology and examined the trends of estimated disaster impact. The results indicate, in total, the global aggregate of damages is about US\$742 billion, losses are US\$360 billion, and total impacts are estimated close to US\$680 billion, in 2007 value. While geophysical disasters are most costly in terms of absolute value for damages, losses, and total impacts, meteorological disasters have the highest impact multiplier of 2.02, indicating that damages and losses can spread to a wider extent through interdependency of economic activities. Moreover, the analysis indicates a growing trend of economic impacts, such as damages, losses, and total impacts, over time using all the 184 events, whereas the trends of damages and losses are statistically significant with linear regression lines. The impact multiplier of the globally aggregated results over the period becomes nearly two, implying that on average the losses caused by a disaster can become doubled through the interdependencies of an economy. Furthermore, the investigation of economic impacts and development level was carried out to see whether or not an inverted ‘U’ curve relationship between total impacts and income level can be observed. The statistical analyses, however, found that inverted U curve relationship, or more generally quadratic relationship, is not statistically significant for total and each type, while climatological, geophysical, and hydrological disasters show a negative linear relationship, confirming the traditional disaster theory, indicating lower-income countries are more vulnerable to higher-order effects than in middle- or higher- income countries. These results conflict with Kellenberg and Mobarak’s (2008) study, in which they use the number of casualties as the disaster impact.

The results in this paper were derived from the damage data of EM-DAT and NatCat database and using SAM for each country in each decade. These damage data and SAMs are highly aggregated without having any sector-level information. For an analysis of historical trends and for international comparison, the aggregation level in this study is acceptable due to the data availability. On the other hand, further detailed analysis, based on disaggregated sectors and/or space, can reveal a more thorough and comprehensive figure of disaster impacts, as presented in a companion paper ‘Impact

Estimation Methodology: Case Studies.’ While more sophisticated analysis requires further precise numerical input data (West and Lenze, 1994), some standardized framework, such as the ECLAC methodology (UN ECLAC, 2003), can guide us on how to gather the more detailed data in a consistent way for future disasters. And, if some common economic model of nations, such as SAM with some level of disaggregation, becomes available, the estimation and examination of disaster impacts will provide not only a clearer and more complete picture, but also a broader and more robust picture of what happens during a disaster. In this regard, the role of international organizations is particularly important.

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Appendices

Appendix 1. Description of Social Accounting Matrix

Social accounting matrix (SAM) was developed by Stone (1961) and further formalized by Pyatt and Thorbecke (1976) and Pyatt and Roe (1977) for policy and planning purpose. SAM is an extended version of IO (and more closely to Miyazawa formulation above), and the structure of a typical SAM includes IO accounts as production activities. Similar to IO analysis, the accounting multiplier matrix can be derived in the following way. The relationships in SAM can be transformed into the equation below:

$$\begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \end{pmatrix} = \begin{pmatrix} \mathbf{X}_{11} & \mathbf{0} & \mathbf{X}_{13} \\ \mathbf{X}_{21} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_{32} & \mathbf{X}_{33} \end{pmatrix} \begin{pmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \\ \mathbf{f}_3 \end{pmatrix}$$

where \mathbf{x}_1 is gross output, \mathbf{x}_2 is income of factors, \mathbf{x}_3 is income of private sector (including household and companies), \mathbf{X}_{11} is transaction between production activities (input-output relationships), \mathbf{X}_{13} is private consumption, \mathbf{X}_{21} is value added payments, \mathbf{X}_{32} is income to private sector, \mathbf{X}_{33} is inter-institution transfer, \mathbf{f}_1 is final demand for production activities, \mathbf{f}_2 is final demand for factor, and \mathbf{f}_3 is final demand for private sector. Then, equation (8) can be rewritten with direct input coefficient matrix as follows:

$$\begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \end{pmatrix} = \begin{pmatrix} \mathbf{A}_{11} & \mathbf{0} & \mathbf{A}_{13} \\ \mathbf{A}_{21} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{32} & \mathbf{A}_{33} \end{pmatrix} \begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \end{pmatrix} + \begin{pmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \\ \mathbf{f}_3 \end{pmatrix}$$

Solving this yields the accounting multiplier matrix:

$$\mathbf{x}_n = (\mathbf{I} - \mathbf{A}_n)^{-1} \mathbf{f}_n = \mathbf{M}_a \mathbf{f}_n$$

where $\mathbf{x}_n = \begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \end{pmatrix}$, $\mathbf{A}_n = \begin{pmatrix} \mathbf{A}_{11} & \mathbf{0} & \mathbf{A}_{13} \\ \mathbf{A}_{21} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{32} & \mathbf{A}_{33} \end{pmatrix}$, $\mathbf{f}_n = \begin{pmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \\ \mathbf{f}_3 \end{pmatrix}$, and \mathbf{M}_a is the accounting

multiplier matrix. Use of SAM for impact analysis is similar to IO, changes in final demand lead to changes in output through accounting multiplier matrix.

Appendix 2. Statistical Analysis of Disaster Impact Trends

The trend analysis of disaster impacts, such as damages, losses, and total impacts, is performed with the following model:

$$DI_t = \beta_0 + \beta_1 \cdot t + \varepsilon_t$$

where DI_t is the disaster impact (in constant 2007 US\$ million) at t , t is year. The results of regression analysis are summarized in Table A2-1. All the coefficients are statistically significant at 5% level. While the values for goodness of fit (R-squared) are relatively small, the sign of β_1 for all three cases are positive, as expected, indicating the increasing trends of disaster impacts. However, these results change with the normalization of disaster impacts.

Table A2-1: Time Series Analysis of Disaster Impacts (All Events)

	Damages	Losses	Total Impacts
Intercept	-1325340** (567477)	-635467** (269310)	-1165020** (511800)
Year	676.165** (286.026)	324.245** (135.741)	594.648** (257.963)
Observations	46	46	46
Durbin-Watson Statistics	2.111	2.094	2.181
F-value	5.588**	5.706**	5.314**
R-squared	0.11	0.11	0.11

** : Significant at 5% level.

Standard errors in parentheses.

Table A2-2 displays the results with normalized disaster impacts data. Normalization was carried out through dividing the value of disaster impact by the world GDP at respective year. Thus, the dependent variable is now the share (%) of disaster impact over world GDP. The results indicate that damages and losses have statistically significant linear trends over years with 10% level, whereas total impacts appear showing no linear trend with the coefficients and the model (F-value) indicating statistically not significant at any level.

TableA2-2: Time Series Analysis of Normalized Disaster Impacts (All Events)

	Damages	Losses	Total Impacts
Intercept	-0.0265* (0.014)	-0.0122* (0.007)	-0.0195 (0.013)
Year	1.36E-05* (0.00001)	6.30E-06* (0.000003)	1.01E-05 (0.00001)
Observations	46	46	46
Durbin-Watson Statistics	1.77503	1.78751	1.81422
F-value	3.542*	3.419*	2.411
R-squared	0.074	0.072	0.052

*: Significant at 10% level.

Standard errors in parentheses.

Appendix 3. Statistical Analysis of Inverted U Curve Relationship

The relationship between GDP impacted (total impacts divided by GDP) and GDP per capita at respective year is analyzed with the following linear and non-linear (quadratic) functions:

$$GDP_impact_i = \alpha_0 + \alpha_1 \cdot \ln(GDP_per_capita_i) + \varepsilon_i ; \text{ and}$$

$$GDP_impact_i = \beta_0 + \beta_1 \cdot [\ln(GDP_per_capita_i)]^2 + \beta_2 \cdot \ln(GDP_per_capita_i) + \varepsilon_i$$

If an inverted U curve relationship existed, the signs of coefficient should be $\beta_1 < 0$ and $\beta_2 > 0$ in the second form. The results of regression analysis are summarized in Table A3-1 for all the events. While in the linear model the value of intercept is statistically significant, the t-value of slope coefficient and F-value are not, indicating no specific trend is found. As for the non-linear model, all the coefficients are statistically insignificant, implying that the inverted U curve relationship cannot be found. While statistically insignificant, the signs of coefficient in the non-linear model suggests inverted U curve, with the turning point at US\$ 1,281.

Table A3-1. Regression Results of Relationship between Impact on GDP and Income Level (all events)

	All Events	
	Linear Model	Non-Linear Model
Intercept	0.210*** (0.079)	-0.416 (0.414)
[ln(GDP_per_capita)]^2	- -	-0.010 (0.007)
ln(GDP_per_capita)	-0.014 (0.010)	0.150 (0.107)
Observations	184	184
F-Value	1.846	2.117
R-squared	0.010	0.023
Implied Turning Point (GDP per capita; 2007 US\$)	-	1,281
Curve Shape	-	Inverted U

*** Significant at 1% level.

Standard errors in parentheses.

Table A3-2 through Table A3-5 show the results for different disaster types. While no statistically significant trends are found with all events, climatological, geophysical, and hydrological events found the linear relationship with a negative slope between disaster impact and income level. Meteorological events do not have any statistically significant results either with linear or non-linear model. While any of disaster types found no statistically significant results with non-linear model, their values for goodness of fit (R-square) are always slightly larger (better) than the linear model counterpart. This implies that non-linear model has greater explanation power over observations than linear model does, for each type of disaster and for overall. Adding more observations might bring more concrete results for this type of analysis.

Table A3-2. Regression Results of Relationship between Higher-Order Effects and Income Level (climatological events)

	Climatological Events	
	Linear Model	Non-Linear Model
Intercept	0.204** (0.079)	-0.289 (0.420)
[ln(GDP_per_capita)]^2	- -	-0.008 (0.007)
ln(GDP_per_capita)	-0.019* (0.010)	0.107 (0.106)
Observations	27	27
F-Value	3.328*	2.409
R-squared	0.117	0.167
Implied Turning Point (GDP per capita; 2007 US\$)	-	925
Curve Shape	-	Inverted U

* Significant at 10% level.

** Significant at 5% level.

Standard errors in parentheses.

Table A3-3. Regression Results of Relationship between Impacts on GDP and Income Level (geophysical events)

	Geophysical Events	
	Linear Model	Non-Linear Model
Intercept	0.427** (0.172)	-0.213 (0.925)
[ln(GDP_per_capita)]^2	- -	-0.010 (0.014)
ln(GDP_per_capita)	-0.040* (0.021)	0.121 (0.228)
Observations	35	35
F-Value	3.401*	1.923
R-squared	0.093	0.107
Implied Turning Point (GDP per capita; 2007 US\$)	-	472
Curve Shape	-	Inverted U

* Significant at 10% level.

** Significant at 5% level.

Standard errors in parentheses.

Table A3-4. Regression Results of Relationship between Impacts on GDP and Income Level (hydrological events)

	Hydrological Events	
	Linear Model	Non-Linear Model
Intercept	0.212*** (0.056)	0.598* (0.320)
[ln(GDP_per_capita)]^2	- -	0.007 (0.006)
ln(GDP_per_capita)	-0.022*** (0.008)	-0.126 (0.085)
Observations	50	50
F-Value	8.14***	4.862**
R-squared	0.145	0.171
Implied Turning Point (GDP per capita; 2007 US\$)	-	10,380
Curve Shape	-	U

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Standard errors in parentheses.

Table A3-5. Regression Results of Relationship between Impacts on GDP and Income Level (meteorological events)

	Meteorological Events	
	Linear Model	Non-Linear Model
Intercept	0.212 (0.180)	-0.638 (0.950)
[ln(GDP_per_capita)]^2	- -	-0.014 (0.0160)
ln(GDP_per_capita)	-0.008 (0.023)	0.216 (0.247)
Observations	72	72
F-Value	0.119	0.475
R-squared	0.002	0.014
Implied Turning Point (GDP per capita; 2007 US\$)	-	1,735
Curve Shape	-	Inverted U

Standard errors in parentheses.